Suicidality and Mood: The Impact of Trends, Seasons, Day of the Week, and Time of Day on
Implicit and Explicit Cognitions

René Freichel¹, Brian O'Shea^{1,2}

¹Department of Psychology, University of Amsterdam

²Department of Psychology, Harvard University

Author Note

Correspondence concerning this article should be addressed to:

Brian A. O'Shea,
Department of Psychology, University of Amsterdam,
Roetersstraat 15, 1018 WB,
Amsterdam, The Netherlands
Email: b.a.oshea@uva.nl

Abstract

Decades of research have established seasonality effects on completed and attempted suicides, with an increase in rates during spring and early summer. Using more than six years of data (April 2012 – November 2018), we used new Prophet models to forecast mood and explicit and implicit measures of self-harm among an online community sample residing in the US and UK ($N > 7,975$). We decomposed the time series into trends across the years, within years (seasons), weekly, and daily seasonal patterns. Across all outcomes, the long-term changes across the years and the seasonal patterns show the strongest variation on explicit and implicit cognitions, followed by the time of day (negative cognitions peaking around 4 am – 5 am), with the day of the week showing the weakest effects. The data show a general increase of negative cognitions across the six years, paralleling trends in suicide rates and depression prevalence in the US and UK. Autoregressive-integrated moving average (ARIMA) models showed seasonality effects for mood and desire to die among US, UK, and Canadian respondents ($N > 10,445$), particularly in the group of respondents who previously made a suicide attempt. Negative cognitions were generally the lowest in summer (June) and peaked in winter (December). These negative cognitions precede the rise in suicidal behaviors during spring and early summer. We discuss potential reasons for lagged effects of negative cognitions on suicidal behavior and implicit cognitions, which may be crucial for theoretical advancements. Our findings have implications for the clinical risk assessment of patients with a history of suicide attempts and public policies regarding the availability of health services.

Keywords: Seasonality, Suicide, Self-Harm, Implicit Cognition, Time-Series

Suicidality and Mood: The Impact of Trends, Seasons, Day of the Week, and Time of Day on Implicit and Explicit Cognitions

Suicide is a major cause of mortality worldwide, and it constitutes a significant public health problem¹. In the United States (US), suicide was the 10th leading cause of death in 2016² and it has steadily increased 35% from 1999 to 2018³. Similar increases in suicide rates were shown in the United Kingdom (UK)⁴. Importantly, these trends are consistent with a general worsening of mental health. Depression prevalence has increased significantly in the US⁵ and some studies suggest a similar increase in depression and anxiety over the past decade in the UK⁶.

The relationship between depression and suicide risk has been extensively studied. As widely noted, a history of mental illness, particularly depression, has been shown to be strongly related to suicidal ideation and suicide attempts⁷. Importantly, a history of self-harm behavior is considered to be one of the most important risk factors of suicide^{8,9} with a large proportion of reported self-harm and psychiatric comorbidity in suicides¹⁰. Identifying temporal periods with increased suicide risk and understanding how time can interact with underlying risk factors of suicide, such as past suicide attempts is highly relevant for clinicians and researchers. Moreover, a greater understanding of temporal variation in implicit and explicit self-harm cognitions may aid public health policies towards developing suicide prevention programs¹¹.

Yearly Seasonality of Suicides and Suicide Attempts

Research on the impact of external time points such as traumatic events¹², negative or adverse life events¹³, and economic crises¹⁴ as precipitants of suicide attempts have been integrated into a broader discussion about seasonal patterns of suicide. Most studies examining seasonality effects report a consistent increase in suicides and suicide attempts during spring¹⁵ and early summer¹⁶. This seasonal variation of suicide is typically found in both men and women; however, some studies report stronger seasonal effects for men than women^{17,18}. Notably, female suicide attempts are estimated to be three to four times higher than men's¹⁹, whereas completed suicides occur primarily in men and are up to four times more prevalent than female suicides^{20,21}.

Recent studies on the origins of seasonal patterns of suicide focus on the role of mood. A debated hypothesis is that an exacerbation of mood disorders (e.g., major depression and bipolar disorder) in spring may trigger seasonal suicide peaks²². Consistent with this theory, some studies demonstrate an association between mood disorders and increased suicide risk in spring^{23,24}. Mood disorders (e.g., seasonal affective disorder) have been also related to sunlight

deprivation in winter months^{25,26}. These seasonal changes with a winter lowering of mood have been further replicated in non-clinical samples²⁷ and are associated with a wide range of factors, including vitamin D deficiency²⁸. Importantly, little theoretical and empirical advancement has been made to explain why attempted and completed suicides rise in spring and early summer. Our study aimed to test a potential mechanism through which negative cognitions in winter may exert lagged effects on suicidal behavior in spring.

Weekly and Daily Patterns

Seasonal fluctuations of death by suicide have been widely studied. However, much less is known about patterns concerning the days of the week and the time of the day. A study of a Danish population showed more suicide attempt admissions during weekends both among men and women with and without mood disorders²⁹. Other studies showed that suicides occurred most frequently on Sundays³⁰ and Mondays^{31–33}. When seasonal differences were taken into account, studies showed a peak on Monday in summer and a peak on Thursday in winter³⁴. These effects of the day of the week appear unrelated to the method of suicide and sex.

A less extensively studied area of research concerns the effects of time of the day on suicides. The results for patterns on time of the day are mixed but suggest that both attempted and completed suicides may be affected by diurnal and circadian rhythms: Several studies on suicide attempts in diverse populations showed that suicide attempts occurred most frequently during evenings and nights^{33,37,38}. The number of completed suicides over the course of the day shows a peak during the morning hours^{39,40} that is not affected by age or gender⁴¹. However, as noted by Preti & Miotto (2001)³⁹, the observed variation in this study was based on the time of death and not the time of the suicidal act, which may precede it by a significant period.

Temporal Patterns in Implicit Measures of Self-Harm and Suicide

Existing research on seasonal and time effects on suicide almost exclusively focused on completed suicides (death statistics, epidemiological studies) and suicide attempts (hospitalizations, medical records, health care data). Some findings in the literature on seasonality of mood showed a lowering of self-reported mood during winter which may be related to seasonal affective disorder⁴². In addition to mood, suicidal thoughts and behaviors were shown to be associated with seasonality in clinical samples of patients diagnosed with major depressive disorder⁴³ and bipolar 1 disorder⁴⁴. Consistent with these results, self-reported measures of eveningness (i.e., a tendency to remain active at night) and decreased rhythmicity

(i.e., lifestyle irregularity) were shown to be associated with suicidality⁴⁵. However, the existence of temporal patterns (seasonality, day of the week, time of the day) in explicit self-report measures of self-harm and suicide remains largely unknown.

Another class of measures rely on reaction times and capture more automatic cognitive biases. These implicit measures have recently also shown promise in suicide research. Implicit associations with self-harm and suicide were shown to be robust and correlated with specific types of self-harm behavior⁴⁶ and predictive of the occurrence of suicide ideation and future suicides^{47–49}. The self-harm and death Implicit Association Tests (IATs) are commonly used to assess self-harm associations which were shown to be increased in suicide attempters compared to a non-suicidal sample⁴⁶. Although little is known about temporal patterns of implicit self-harm associations, time-series analyses on implicit social-group attitudes showed evidence for both stability and long-term change over a 10-year period⁵⁰. Our study is the first to examine the temporal dynamics of implicit self-harm associations and their relationship to explicit measures.

Current Study

Our study aims to assess long-term trends and the effects of seasons, day of the week, and time of the day on mood, desire to die, desire to self-injure and implicit measures of self-harm (negative cognitions). Our analyses aim to test the generalizability of time effects found at the level of suicide attempts and completed suicides. In accordance with the literature, we predicted that mood, explicit suicidality and implicit self-harm associations to increase between 2012-2018 and for a peak in negative cognition in spring or early summer. We predicted negative cognitions peaking towards the end of the week with a peak on Sunday or Mondays and during night hours.

Methods

Data Source/Respondents

We used data from the PIH database (www.projectimplicithealth.com) and included responses between April 2012 and November 2018. All respondents voluntarily visited the PIH website and chose to complete a self-harm IAT. We included data from participants who were residing in the US, the UK, and Canada. Given the small sample size for other countries and the potential influence of cultural differences and latitude (e.g., difference between countries north and south of the equator) on seasonal patterns, we decided to not include any other countries. After standard data cleaning procedures were performed (see below), the final sample was 10,448. Table S1 in the Supplementary Materials summarizes the demographic distribution for the two primary analyses. Our sample is generally young ($M = 26.73$, $SD = 10.76$) and 71% of all respondents are female. Importantly, our sample showed significant variance with respect to the self-reported history of self-injurious thoughts and behaviors. Approximately 30% of all respondents reported a past suicide attempt. Notable, the proportion of respondents who reported a past suicide attempt, engaged in non-suicidal self-injury or made a past suicide plan, did not sustainably differ throughout the years, months, days, or hours (see Figure S1-S4).

After providing informed consent, all participants were randomly assigned to one of four IATs: Cutting ($n = 1143$); Suicide ($n = 2674$); Death ($n = 2712$); brief Death IAT ($n = 1449$). The four IATs have different target words and images (i.e., cutting/no cutting; suicide/life; death/life) that are each presented on a screen with attributes (i.e., me/not me). For instance, the death IAT with the “death” category contains target examples of “death” (e.g., die, funeral) and “life” (e.g., live, survive). The categories differ between the IATs (suicide IAT: suicide category (e.g., hanging, overdoses), cutting IAT (e.g., images of cut skin and uncut skin). The IATs, explicit measures, and sociodemographic questions were presented in a random order. All explicit measures and sociodemographic questions were identical across the four IATs.

Measures

IATs

The selected IATs (Greenwald et al., 1998) measure implicit cognition about self-harm in a computerized task. Participants are instructed to distinguish and correctly classify different self-harm-related stimuli (i.e., cutting, suicide) from non-self-harm stimuli (i.e., life). By pressing a left (i.e., “Life-Me”) or right (i.e., “Suicide-Not Me”) keyboard key, participants are

instructed to assign the words or images that appear at the center of the screen into the appropriate categories as fast and as accurately as possible. Halfway through the task, the key assignments switch, resulting in new attribute pairings for the left (i.e., “Suicide-Me”) and right (i.e., “Life-Not Me”) keyboard keys. A red “X” appears if participants incorrectly assigned the target word. The brief death IAT is shorter than the IAT and only presents two categories on the screen without the “not me” category⁵². Respondents are instructed to use one button to classify the stimuli that match the category labels and another button for stimuli that do not match the labels. This shorter and simpler version of the death IAT was previously shown to be reliable and valid in distinguishing between suicide attempters and non-attempters⁵³.

The IATs scored using the most common method described by Greenwald and colleagues (2003). This standardized difference score (D-Score) was computed for each participant who fully completed the IAT. Essentially, this score represents the strength of association between two concepts (i.e., death and life) and me⁵². In all tests, positive D-Scores reflect the self-harm and me associations, while negative scores indicate the non-self-harm (i.e., life) and me associations. To exclude responses with a high error rate or too fast responses, we used the criteria described in Glenn et al. (2017) that are slightly stricter than the recommendations from Greenwald et al. (2003): The IAT scores of participants were removed if their reaction times (RT) or error rates passed a threshold in critical blocks (> 25% of RT faster than 300ms; > 40% trial errors) or overall (> 10% of RT faster than 300 ms; > 30% trial errors).

Explicit self-report measures

We selected three explicit measures (see Table 1) that were given to participants before and after each IAT to examine potential iatrogenic effects⁵⁵. The three items assessed participants’ desire to self-injure, desire to die, and their current mood. To increase the reliability, we average the pre- and post-IAT measures.

Demographic variables

Sociodemographic information, including age, gender, educational background, ethnicity, race, and country of residence was collected from participants.

Table 1*Items to assess Iatrogenic Effects and their respective Scale and Measured Construct.*

Item	Scale	Construct
How would you rate your mood right now?	-3 (Extremely Positive) -2 (Moderately Positive) -1 (Slightly Positive) 0 (Neutral) 1 (Slightly Negative) 2 (Moderately Negative) 3 (Extremely Negative)	Mood
How much do you want to hurt yourself right now?	0 (Not at all) 1 (Slightly) 2 (Moderately) 3 (Strongly) 4 (Extremely)	Desire to self-injure / Desire to hurt oneself
How much do you want to die right now?	0 (Not at all) 1 (Slightly) 2 (Moderately) 3 (Strongly) 4 (Extremely)	Desire to die

History of self-injurious thoughts and behaviors

To assess participants' history of self-injury, we used responses from the abbreviated version of the Self-Injurious Thoughts and Behaviors Interview (SITBI). The SITBI was shown to be a reliable tool (inter-rater reliability: average $\kappa = .99$, $r = 1.0$; test-retest reliability: $\kappa = .70$, $ICC = .44$) to assess self-injurious thoughts and behaviors⁵⁶. We used three items from the entire interview to assess a history of suicide attempts ("Have you ever made an actual suicide attempt, where you wanted to kill yourself, even just a little?"), a past suicide plan ("Have you ever actually made a plan to kill yourself?"), and a history of non-suicidal self-injury ("Have

you ever done anything to purposely hurt yourself without wanting to die (for example cutting or burning your skin)?”). Participants were asked to respond to these questions on a dichotomous scale (Yes / No). Based on these items, we compared three groups of respondents depending on the severity of self-injurious thoughts and behaviors (Group 1: past suicide attempt, Group 2: a history of suicide plans or non-suicidal self-injury, Group 3: no previous self-harm, suicidal thought or behavior).

Time-series analysis

Prophet model

The open-source Prophet software is available in both R and Python and was designed to forecast time series data⁵⁷. The Prophet model adopts a Bayesian curve fitting method for forecasting a time series model with three main components: trend (non-period changes across the entire time interval), period changes (e.g., daily, weekly, yearly seasonal patterns), and effects of holidays. Prophet uses a posterior probability estimation (MAP) method or full Bayesian statistical inference that includes Markov Chain Monte Carlo (MCMC) sampling.

The Prophet model has significant advantages in time series that have missing data, shifts in its trend, and strong seasonal components. As we have several seasons of data to train the model, Prophet allows us to extract period changes on different time scales. Thus, these advantages make Prophet particularly suitable for the analysis of the self-harm IAT data. Importantly, Prophet models have successfully been applied in detecting trends and daily, weekly, and yearly seasonal patterns⁵⁸, and were shown to outperform ARIMA⁵⁹.

To obtain accuracy estimates for our Prophet forecast, we used a cross-validation procedure with independent training and test sets. For the cross-validation, we used the data from April 2012 to November 2017 as the training data and tested the forecast in the one-year period from December 2017 to November 2018 (validation set). For the final forecast of all outcome measures, we used all available data from April 2012 to November 2018 to forecast the one-year period until November 2019 (testing set). We chose to forecast a one-year period as the validation set and as a consequence, all forecast accuracy estimates refer to one year. See Supplemental Materials Section 2 for further details validating the accuracy of the Prophet models used with the current dataset.

ARIMA model

ARIMA models use three parameters to describe a time series: p (autoregressive terms), d (non-seasonal differences), q (moving averages terms).

ARIMA model: (p, d, q)

In seasonal time series, seasonal ARIMA models (SARIMA) incorporate both seasonal and non-seasonal components. In addition to the ARIMA parameters, they include P (seasonal autoregressive terms), D (seasonal differences), Q (seasonal moving-average terms), and S (periodic terms). In our analysis using ARIMA, the occurrence of variations in the outcomes is over the monthly period ($S = 12$).

SARIMA model: $(p, d, q) \times (P, D, Q) S$

Given the irregular intervals between responses for certain times of the day and missing responses on weekdays during certain months, we aggregated the data for every month for the analyses with ARIMA models. Given the large sample size in our data, the aggregated monthly estimates rely on a moderate number of observations (average per month for the entire sample: 132.66) with at least 38 observations on average per month within the different groups of respondents.

We used the auto-ARIMA function and explicitly allowed seasonal components to select the model parameters that defined the model order for the forecast. The auto-ARIMA function will select a seasonal model with the respective components (P, D, Q, S) if there are seasonal yearly effects in the data. We used log-likelihood ratio tests to compare seasonal ARIMA models with non-seasonal ARIMA models to test whether clear seasonality effects were present. The advantage of using the auto-ARIMA function is that all model parameters are automatically selected based on the overall model fit, as indicated by the Akaike information criterion (AIC).

Using the Augmented Dickey-Fuller test, the auto-ARIMA model automatically chooses the order of first differencing required to make the time series stationary. We used a non-stepwise auto-selection of models, thus searching over all possible model specifications. To train the ARIMA models, we used data from all months starting in December 2012 until November 2018 to ensure the models use the maximum amount of information to achieve their predictive power. The ARIMA models have the advantage of dealing with temporal

autocorrelations due to their flexibility⁶⁰. Importantly, ARIMA models are commonly used in applied time series analyses to characterize seasonality effects, such as in patterns of suicides⁶¹.

Granger models of predictive causality

In an exploratory fashion, we aimed to examine the temporal relationship between changes in explicit and implicit negative cognitions. As three of the selected IATs primarily focus on death and suicide, we exclusively tested directed temporal relationships between desire to die and the IAT D-Score at the level of months, weekdays, and hours. Granger causality tests have been successfully used to examine whether changes in explicit social-group attitudes precede changes in implicit attitudes⁵⁰ however little is known about the relationship for suicide cognitions. Using Wald tests, we compared restricted prediction models (e.g., desire to die is explained by lags of desire to die) with unrestricted prediction models (e.g., desire to die explained by lags of desire to die and the lags of implicit IAT D-Scores). To rule out reverse causation, we always tested both directions of change to examine whether a) explicit desire to die precedes the implicit association with death/suicide and b) implicit association precedes the explicit desire to die. When only one direction is significant, then this finding indicates the potential lagged effects with changes in one variable preceding another.

Data analytic plan

We used two advanced analytical approaches, namely Prophet models and ARIMA models to examine the effect of temporal patterns on explicit and implicit cognition. To obtain accurate time and date information, we converted participants' local time and date to Eastern Standard Time using the zip-code and country of residence information. For our analyses we divided the sample based on the availability of accurate time and date information: We included participants who provided valid zip code information in the US ($n = 7327$) and participants from the UK ($n = 651$) in our analyses with the Prophet models (sample 1). As the Prophet model examines seasonal patterns on the level of times of the day and days of the week, accurate time and date information are required. MCMC sampling was used to estimate uncertainty intervals.

For our analyses with the ARIMA models, we included all participants (combined samples 1 and 2, $N = 10448$) from the US, UK, and Canada as we aggregated the data to monthly intervals to obtain more accurate estimates. Thus, given the aggregation to monthly intervals, it was not necessary to convert the time and date information of respondents with a residence in Canada based on their time zone information. To replicate the yearly patterns

found in the Prophet models using a different methodology, we selected ARIMA models that allowed us to statistically test whether the time series can be described using seasonal or non-seasonal parameters.

Additional t-tests were used as a convergent method of testing differences between the months with the lowest and highest outcome scores as indicated by the seasonal patterns. This served as a simple statistical method to ensure that the seasonality effects manifest themselves in a statistically significant overall difference in the outcome scores between months with the yearly minimum and the yearly maximum. We controlled for the false discovery rate using the method by Benjamini and Hochberg (1995) in the t-tests that were used for multiple comparisons of two months within the three groups and four outcome measures. All analyses were performed in RStudio (R version 4.03). The pre-processed dataset without zip-code information and relevant data analyses scripts used in this study can be accessed via the Open Science Framework (<https://bit.ly/3s3rTdh>).

Results

Trends and Seasonal Patterns in Explicit and Implicit Measures

First, we forecasted the distribution of all four outcome variables and decomposed it into trends across the years, yearly seasonality, weekly, and hourly effects. At a given time, the estimated outcome scores are the sum of the respective trend, yearly, weekly, and daily effects. The Prophet models provided a good fit to the data with a similar performance in both training and test sets (see Table S2 in the Supplementary Materials).

Trends

The Prophet models showed upwards trends in all outcome variables from 2012 to 2018 and an expected increase in the forecasted period until November 2019 for all outcome variables (see Figure 1). Importantly, the proportion of respondents who report a past suicide attempt, a history of non-suicidal self-injury and no history of self-harm remains generally similar across the years (see Figure S1), the months (see Figure S2), weekdays (see Figure S3) and the time of the day (see Figure S4). To quantify the trends in negative mood, the desire to die, the desire to self-injure, and the IAT D-Scores, we computed the percentage of average increases during the entire period (April 2018 – November 2018) and the forecasted period (see Table 2). The observed increases between April 2012 and November 2018 are particularly

strong for both negative mood (5.90% average yearly increase) and the desire to die (6.38% average yearly increase).

We also observed similar patterns when fitting separate Prophet models to the three different groups (Figure S5). The increases for both the desire to self-injure (4.29% average yearly increase) and the IAT D-scores (2.73% average yearly increase) are significantly lower. Moreover, we observed a decline in the slope of the increase in the desire to die and the IAT D-Scores in 2016 which may explain the rather low forecasted increases in the Prophet trends (desire to die: 1.16 %, IAT D-Scores: 0.06 %). MAP estimations, which generally show stronger increases over time (Table S3). Figures for the averaged means across the years for the combined sample (Figure S16) can be found in the Supplementary Materials.

Figure 1

Trends Decomposed from the Prophet Forecast for Mood, Desire to Hurt Oneself, Desire to Die and the IAT D-Scores

Note. The graphs show both the trends in the training data (continuous, $N > 7912$) and the expected trend in the forecast for one year (dashed).

Table 2*Trends in Negative Mood, Desire to Die, Desire to Self-Injure and the IAT D-Scores*

	Total % Increase 2012 – 2018	Average % Yearly Increase 2012 - 2018	Forecasted Change until November 2019
Negative Mood (SD)	31.74%	5.90% (7.75%)	-3.40%
Desire to Die	43.83%	6.38% (5.85%)	0.15%
Desire to Hurt Oneself	28.05%	4.29% (4.44%)	0.19%
IAT D-Scores	15.75%	2.73% (4.35%)	0.84%

Note. The total and average % yearly increase was calculated starting April 2012 and includes the one month forecast for December 2018. The standard deviation for the average yearly increase is indicated in parentheses. The forecasted increase refers to the time period from January 2019 to November 2019. Markov Chain Monte Carlo sampling was used.

Yearly Seasonality

The Prophet model forecasts clearly show yearly seasonal changes throughout the year (see Figure 2). There is an apparent minimum in early summer (June) and maximum in winter (December) for mood, desire to die, and desire to self-injure. We observe a slightly shifted seasonal pattern in the implicit IAT D-Scores that peak in February and are lowest in September. Based on this shifted pattern, we used Granger causality tests at lags of two and three months. This exploratory analysis showed a significant effect of the desire to die on the IAT score only at a lag of 2 months ($F = 5.73, p < 0.01$). There were no significant effects for the prediction of the IAT D-Score from the desire to die at any of the lags (see Table S5). These results suggest that change in the explicit desire to die likely precedes the implicit change.

We quantified the yearly seasonal changes as the absolute difference between the average outcome scores in the months that show the highest and lowest scores (negative mood, desire to die, and desire to self-injure: December – June; IAT D-Scores: February – September). Importantly, the yearly seasonal pattern appears to be the largest compared to all other seasonal patterns (e.g., see negative mood in Figure 3). For a comprehensive overview of the different seasonal patterns for the desire to die, desire to self-injure, and the implicit IAT

D-Scores, see Figures S6, S7, and S8 in the Supplementary Materials that illustrate the patterns on the same scale of the outcome.

Figure 2

Yearly Seasonality Decomposed from the Prophet Forecast for Mood, Desire to Hurt Oneself, Desire to Die and the IAT D-Scores

Figure 3*Yearly, Weekly and Daily Seasonal Patterns for Negative Mood*

Note. The graphs show the yearly (A), weekly (B) and daily (C) seasonal patterns for negative mood on the same scale (-0.25 to 0.25).

Weekly Effects

The effects for the day of the week (see Figure 4) were small compared to all other seasonal components. All outcomes peaked during the beginning of the week (Monday: negative mood; desire to self-injure; Tuesday: desire to die, D-Scores) and were lowest towards the end of the week (Thursday: desire to die, desire to self-injure, Friday: negative mood, Saturday: D-Scores). Exploratory tests of granger causality showed no significant predictions of change at lags of 1 and 2 days – suggesting that both the desire to die and the implicit association change independently (see Table S5).

The visualizations for both the weekly seasonal patterns in the Prophet models (see Figure S10) and the mean results (see Figure S18) for the three groups can be found in the Supplementary Materials.

Figure 4

Weekly Seasonality Decomposed from the Prophet Forecast for Mood, Desire to Hurt Oneself, Desire to Die and the IAT D-Scores

Daily Effects

For the daily seasonality (see Figure 5), we observed a similar pattern in all outcomes with peaks during the night hours (4 am – 5 am) and a minimum during the afternoon/evening hours. When examining the range of the daily seasonal patterns, they are similarly impactful to both trends and yearly seasonal patterns (e.g., Figure 3). The exploratory granger tests of causality showed that the explicit desire to die predicts the implicit IAT D-Score at a lag of one hour. The reverse direction was not significant indicating that the change in the implicit measure likely follows changes in the explicit. There were no significant effects in any direction at lags of two hours (see Table S5). Supplemental visualizations of the daily outcome averages suggest similar patterns with only small increases in all three groups towards the night and early morning hours (see Figure S19 in the Supplemental Materials). Separate Prophet models for the three groups showed rather inconsistent results but we observed general increases during evening and night hours in the group of respondents that have reported making a suicide attempt (see Figure S11 in the Supplemental Materials).

Figure 5

Daily Seasonality Decomposed from the Prophet Forecast for Mood, Desire to Hurt Oneself, Desire to Die and the IAT D-Scores

Group Comparison in Yearly Seasonality Effects

Our forecast for the sample with accurate time and date information showed nested seasonality effects with a strong yearly seasonal pattern. Thus, we aimed to further examine how risk factors (past suicide attempt, suicide risk (suicide plan and/or non-suicidal self-injury) interact with these yearly seasonal changes. Table 3 summarizes the results of the ARIMA models that showed clear seasonality effects for mood and the desire to die in the group of respondents that reported making a suicide attempt and the entire sample. The ARIMA forecasts for the yearly seasonality effects are shown in the Supplementary Materials for all seasonal ARIMA models for the entire sample (mood: S12, desire to die: S13) and the group of respondents that reported making a suicide attempt (mood: S14, desire to die: S15). Importantly, we did not find evidence for yearly seasonality effects in negative mood and the desire to die in respondents that reported a history of non-suicidal self-injury or a previous suicide plan. The ARIMA models provided no evidence for yearly seasonality effects in any of the other groups for the desire to self-injure and the IAT D-Scores. Importantly, there were no substantial differences between the number of respondents within the three groups that could explain these differences (see Table 3). Prophet models that were fitted separately to the three groups (respondents with a previous suicide attempt, suicide plans or non-suicidal self-injury and no history of self-injury) showed similar yearly seasonal patterns, particularly in the group of respondents that reported a previous suicide attempt (see S9 in Supplementary Materials).

Table 3

Results from the ARIMA models and t-tests for all outcomes and groups.

	Entire Sample N = 10448	Suicide Attempt n = 3247	Self-Harm / Suicide Plan n = 3851	No Self-Harm n = 3026
Negative Mood				
ARIMA	Seasonal ***	Seasonal ***	Non-Seasonal	Non-Seasonal
AIC	-31.83	23.29	6.63	22.82
Model	(2,0,0) (0,0,1) [12]	(0,0,0) (1,0,0) [12]	(2,0,0)	(3,0,0)
t-statistic	-4.99**	-2.20*	-2.64*	-2.90*
mean diff. [CI]	-0.36 [-0.5, -0.22]	-0.29 [-0.55, -0.03]	-0.30 [-0.53, 0.08]	-0.38 [-0.64, -0.12]
Cohen's d	-0.27	-0.22	-0.23	-0.30
Desire to Hurt				
ARIMA	Non-Seasonal	Non-Seasonal	Non-Seasonal	Non-Seasonal
AIC	-147.11	-22	-70.32	-164.67
Model	(1,0,0)	(3,0,0)	(1,0,4)	(5,0,0)
t-statistic	-3.36**	-2.38*	-1.45	-0.37
mean diff. [CI]	-0.12 [-0.21, -0.05]	-0.21 [-0.38, -0.04]	-0.08 [-0.20, 0.03]	-0.01 [-0.08, 0.05]
Cohen's d	-0.18	-0.23	-0.13	-0.04
Desire to Die				
ARIMA	Seasonal **	Seasonal **	Non-Seasonal	Non-Seasonal
AIC	-114.75	5.99	-42.08	-92.72
Model	(0,1,1) (1,0,0) [12]	(3,0,0) (0,0,1) [12]	(4,0,0)	(0,0,0)
t-statistic	-4.56**	-3.80**	-1.82	-0.18
mean diff. [CI]	-0.21 [-0.29, -0.12]	-0.37 [-0.56, -0.18]	0.12 [-0.25, 0.01]	-0.01 [-0.12, 0.10]
Cohen's d	-0.25	-0.36	-0.16	-0.02
IAT D-Scores				
ARIMA	Non-Seasonal	Non-Seasonal	Non-Seasonal	Non-Seasonal
AIC	-213.92	-115.75	-133.69	-149.94
Model	(0,0,2)	(4,0,0)	(4,0,0)	(1,1,1)
t-statistic	-4.59**	-1.68	-2.70*	-2.80*
mean diff. [CI]	-0.13 [-0.18, -0.07]	-0.10 [-0.21, 0.02]	-0.12 [-0.21, -0.03]	-0.11 [-0.19, -0.03]
Cohen's d	-0.26	-0.18	-0.26	-0.28

Note. For seasonal models, we used log-likelihood ratio tests to compare the seasonal auto-ARIMA model with a non-seasonal auto-ARIMA model. The p-values for the log-likelihood ratio tests are reported in asterisks (* ≤ 0.05 ; ** ≤ 0.01). The entire sample included respondents with missing SITBI information. The lowest and highest month comparison differed for the different outcome variables (*Negative Mood*, *Desire to Die*, *Desire to Self-Injure*: June – December; *IAT D-Scores*: August - January).

Figure 6

Averaged Monthly Scores for Mood, Desire to Hurt Oneself, Desire to Die and the IAT D-Scores in all Groups

In addition to the ARIMA models, we examined the group means collapsed across all years (see Figure 6) and used two-sample t-tests as a convergent method. First, we collapsed across the groups and years to determine the months for which the outcome variables reach their minimum and maximum. For mood, desire to die, and the desire to hurt oneself, we see a clear pattern with the highest mean scores in December and the lowest in June. The implicit D-Scores showed a slightly shifted pattern with a peak in January and a minimum in August. Thus, we compared the scores on all outcomes and groups during the peak in the summer month (June for mood, desire to die, desire to hurt oneself; August for IAT D-Scores) with the lowest point during the winter months (December for mood, desire to die, desire to hurt oneself; January for IAT D-Scores). We expected the t-tests to show significant differences in those groups and outcomes where the ARIMA models detected seasonalities. Consistent with both the ARIMA results and the decomposed Prophet forecast, we saw significant differences between June and December for mood and desire to die in the group of respondents with a past

suicide attempt. However, the t-tests also suggest significant differences for the desire to self-injure, negative mood and the IAT D-Scores which is inconsistent with the ARIMA results.

Discussion

Our study investigated long-term changes and seasonal patterns in negative mood, explicit and implicit measures of self-harm and suicide (negative cognitions) among a large online community sample. Due to data collection continually running for six years, we were also able to estimate negative cognitions for the day of the week and within the day (hourly).

Trends in Negative Cognitions across Years (2012-2018)

The Prophet models showed clear trends in our data with an increase in respondents' negative mood, desire to self-injure, and desire to die across the six years. This finding is consistent with previous studies showing similar rates of increase in deaths by suicide³, anxiety and depression symptoms⁶³, mood disorders, and suicide-related outcomes (suicide ideation, plans, and attempts from 2005 to 2017)⁶⁴. Although the Project Implicit Health database is not representative, this convergence in yearly trends between the dataset we used here and more objective metrics such as national health records indicates that this online data collection method appears to be capturing meaningful national mental health trends. It is beyond the scope of the current work to explain the worsening trends found in our analyses; however, various explanatory factors have been put forward. These include economic factors, such as growing income-related health inequalities⁶⁵, and psychological distress caused by an increase in loneliness⁶⁶, potentially due to the rise of individualism⁶⁷, and increased smartphone/social media use⁶⁸. Interestingly, we also showed an increase in respondents' implicit associations with self-harm across the years – suggesting that self-harm-related implicit cognition may be a convergent marker for the increase of suicide-related explicit cognitions⁶⁹.

Yearly Seasonality Effects

The primary goal of our study was to test yearly seasonality effects in suicide-related cognitions with hypothesized peaks in spring and early summer which would align with the seasonal patterns of completed and attempted suicide²⁴. The Prophet models did show yearly seasonal patterns for all explicit and implicit measures (based on visual inspection), however, the peak in negative explicit cognitions preceded the suicidal behavior trends, with the highest points in winter (i.e., December) and lowest in summer (i.e., June). The ARIMA models confirmed seasonality effects for negative mood and the desire to die in the entire sample, but

this effect was primarily driven by the group of respondents that reported making a previous suicide attempt.

Inconsistent results were shown for desire to hurt oneself and yearly seasonal patterns were not detected statistically for the self-harm IATs. The divergence of the seasonal patterns found in the Prophet models and the ARIMA models may be partially due to their methodological differences as we aggregated the data to monthly intervals for the ARIMA models. This aggregation to monthly intervals in the ARIMA models likely reduced the variance that can be explained by monthly seasonal patterns. Similarly, the divergence between ARIMA models and the t-tests are likely due to aggregation and our overly simple set-up for comparing the month with highest score to the month with the lowest score. Additionally, t-tests do not take autocorrelations in our time series into account. Moreover, it is important to note that explicit measures may be more reliable than the implicit IAT D-score due to a higher measurement error in implicit measurement⁷⁰. In our study, we used data from four different IATs related to self-harm to increase the total sample size. However, this merging likely added even more measurement error to the data, potentially reducing the likelihood of detecting an effect.

Weekly and Daily Effects

Relative to the yearly seasonality effects, we observe comparably strong daily variation in negative cognitions, while weekly variation was the weakest (see Figure 3, S6-S8). Negative mood and self-harm cognitions peaked late during night or early morning hours – consistent with previous findings showing an increased number of suicide attempts and suicide deaths during night hours³⁷. For daily effects, it appears that changes in explicit responses preceded or paralleled implicit scores. However, this correspondence was not the case when Prophet was used to test for variation in weekly patterns. Overall, as hypothesized, the negative cognitions from this online community sample were similar to clinical observation of increases in suicidal behaviors towards the end of the week and early morning. This finding indicates that continually crowdsourcing explicit and implicit responses may provide an inexpensive method to accurately estimate meaningful weekly and daily behavioral patterns. This may be particularly useful to study groups that are typically difficult to approach (i.e., respondents with a past suicide attempt) and at times that are traditionally difficult to acquire data (i.e., outside of regular working hours).

Explicit Desire To Die Precedes Implicit Self-Harm Associations

Using the Prophet model, the IAT scores showed a peak in February and a dip in September, which clearly lagged behind the high and low points of the explicit responses. Based on the visual inspection of the Prophet models, we used Granger models of causality to test lagged effects at the level of months, weeks and hours for the desire to die. Overall, the results provided by the Granger causality tests are in line with the visual inspection of the Prophet models. Changes in the explicit desire to die were shown to precede the implicit association for both hours (lags of one hour) and months (lags of two months). No lagged effects were found for the days of the week (lags of one and two days) which is consistent with the Prophet results indicating that weekly changes only explain little variance. However, our results are consistent with recent studies showing that explicit responses generally appear to parallel implicit scores when distinct changes in the environment occurred^{71–73}. Future analyses should specifically test whether implicit biases lag, parallel or precede explicit biases and whether these effects are moderated by psychological distance (i.e., concepts more relevant to oneself are expected to show closer parallels in changes than concepts less relevant; see construal level theory⁷⁴). Project Implicit databases have the best potential at answering this important research question due to the large samples gathered over several years.

Why do Negative Cognitions Precede Suicide Attempts and Deaths?

We believe the most crucial finding from our analysis is the rise in negative mood and desire to die, especially among suicide attempters, occurring approximately three to four months before (December) the yearly seasonal peak of suicide attempts and deaths in spring and early summer. Next, we present various speculations as to why there is a lagged effect between negative mental cognitions and suicidal behaviors. We propose a conceptual threshold model of seasonal suicide risk (see Figure 7) that may explain the lag between the rise of negative cognitions in winter and the peak of suicides in spring. We hope that our proposed model can advance suicide theoretical frameworks and inspire future research with the ultimate goal of reducing seasonal suicide attempts and deaths.

First, we show that at risk individuals for suicide gradually get more and more depressed and their desire to die gradually increases as day length becomes shorter (winter solstice). Affected individuals may become severely depressed and experience lack of energy throughout the winter months. Essentially, this period may put them below a threshold of severe suicide risk as the high level of suicidal ideation coincides with a low level of energy. When the days get longer, brighter, and warmer, these changes likely improve an individuals' mood and hence, the most at-risk individuals become slightly less depressed and may gain

more energy to contemplate and plan their method to attempt suicide. Therefore, these improvements now result in them crossing a threshold into severe suicidal risk when a suicide attempt is most imminent. As the summer solstice approaches and passes, it is conceivable that suicidal individuals may go above and beyond a severe suicidal risk due to prolonged days and improved weather. Therefore, severe risk of seasonal suicides occurs when opportune conditions are met, (i.e., not when an individual is the most depressed or the least depressed but somewhere in between).

Figure 7

A Conceptual Threshold Model of Seasonal Suicide Risk

Note. A potential timeline of events (A – E) is shown in the figure. A period with a high-level suicidal ideation, fatigue, and negative mood (i.e., hospital admission, start of medication/therapy treatment); B: The interaction of reduced ideation, increased energy, and improved mood may put individuals within a threshold of high risk of suicide (perhaps comparable to being released from hospital after a suicide attempt or after starting medication for depression); C: Lower ideation and improved mood in summer; D: Increased ideation and lower mood after the summer period.

There are two other situations in the suicide domain where similarly opportune conditions co-occur with increased chance of suicide. (1) Some studies have shown that the risk of suicidal behavior is particularly high during the first month after starting treatment with

antidepressants, especially the first 9 days compared to those who have been taking antidepressants for 90 days or more⁷⁵. Therefore, prior to taking antidepressants, patients may be below the severe risk threshold using the same logic as above. But similar to the weather and environmental changes improving mood, antidepressants likely have a comparable impact on mood improvement, which may put them into the severe risk threshold. However, the longer patients take the antidepressants (>90 days) they may go beyond the severe risk threshold.

(2) There is also evidence that suicide risk peaks shortly after being discharge from psychiatric hospitalization and the risk reduces over time⁷⁶. Similar to medication and seasonal changes, it is likely that the therapy is reducing their negative cognitions, but regardless, they are still at a severe risk until negative cognitions reduce even more. Of course, there may be various other complex reasons for the peak in suicide rates in spring/early summer, such as seasonal changes in bioclimatic factors and social activities.⁷⁷

The Group x Seasonality Interaction – a Contrast Effect?

Using ARIMA models, we found seasonality effects for both mood and the desire to die only in the group of respondents with a past suicide attempt when the entire sample was split into meaningfully distinct groups. This finding is also consistent with the forecasts from the Prophet models suggesting that only a subgroup of respondents that reported making a suicide attempt may be particularly affected by seasonal changes. There may be various explanations to account for this: Recent evidence suggests that within a clinical sample of participants with bipolar disorder, those participants with lifetime suicide attempts were particularly affected by climate and weather changes⁷⁸.

Another speculation for this interaction effect may be the differential impact of seasons on psychosocial well-being in different groups at risk for self-harm and suicide. The lowering of mood⁷⁹, weather changes (i.e. lower temperature and less exposure to sunshine), reduced mobility⁸⁰ and disrupted sleep and waking cycles in winter may particularly affect people with a prior history of severe mental illness, such as a past suicide attempt. Similar reasons may account for the observed seasonality in seasonal affective disorder that is characterized by periods of depression in winter and non-depressed periods in summer⁸¹. To clarify, our results show that negative mood is worse in winter for all respondents independent of their history of self-injurious thoughts and behaviors (Figure S9). However, the strong impact of the winter season on individuals at high risk for suicide may lead to negative cognitions that persist throughout spring – perhaps unconsciously as shown through the lagged IAT scores. In contrast, the mood for individuals at low risk for suicide and with no history of mental illness

likely improves from spring. This divergence and increasing contrast in mood may become more salient for affected individuals compared to those less impacted by seasonal effects and may potentially reinforce negative cognitions through social comparisons (i.e., contrast effects). Future studies should aim to further investigate such potential contrast effects. The COVID-19 pandemic may offer a useful scenario to test this effect as lockdowns have limited the mobility of the entire population, thereby also affecting the increase in social activity during spring.

Limitations and Future Directions

Our findings should be interpreted in light of several limitations. First, the sample in our data is disproportionately young and female, and therefore, it is not representative of the general population. Any conclusions that emerge from a sample consisting of online volunteers may not generalize to other contexts. However, Project Implicit's explicit biases show similar trends over time to nationally representative polls⁵⁰ and various studies have shown that results from Project Implicit samples are associated with meaningful regional outcomes^{82,83}. Second, the responses to the items from the SITBI rely on self-report and should not be considered as established diagnoses. Our sample shows a high prevalence of self-injurious thoughts and behaviors with around 38% of all participants reporting a past suicide attempt or a history of non-suicidal self-injury. This is significantly higher than typical community samples and may be due to the self-selecting nature of PIH samples. However, given the low base rate of suicide in the general population, the results based on our data are valuable as they allow us to gain insights into explicit and implicit suicide cognition in an otherwise difficult to obtain group of respondents. Various studies that aimed to build prediction models to detect suicide attempters apply a commonly used method of oversampling suicide attempters⁸⁴.

Third, our study focused on the temporal patterns in self-harm related implicit and explicit cognitions. Importantly, the reasons for suicidal ideation and suicide attempts are the result of a complex interaction between many factors that cannot be explained solely by temporal patterns. For instance, our study does not take regional differences, climate, or culture into account which may limit the external validity of our findings. Future studies should further validate our forecasts and re-examine the temporal patterns across different clinical domains or disorders (e.g., anxiety, substance abuse) using the existing PIH databases, but also surveys that are representative of the general population. Lastly, future studies should examine whether the described yearly seasonal patterns generalize to other countries, particularly countries in the southern hemisphere.

Concluding Comments

Our study is the first to describe temporal patterns and long-term trends in explicit and implicit measures of self-harm and suicide in an online community sample. Our work extends both epidemiological research on suicide deaths and clinical research on psychiatric inpatients and health care data by using a large online sample. Using state-of-the-art time-series models, we show that a) people with a past suicide are affected by seasonal changes with significant increases in suicide cognition during the winter months, b) there appears to be a latency between the peak of explicit and implicit suicide cognition in winter and the peak in suicide attempts and suicide deaths in spring, c) explicit suicide cognition likely precedes implicit self-harm associations, and d) explicit cognitions towards self-harm and mood are strongest during late night/early morning hours.

These insights are relevant for clinicians in their risk assessment of potential suicide attempts for patients at risk. Given the complex and multifaceted dynamic of suicidal behavior, clinicians should take temporal patterns, in addition to a range of clinical assessments, into account. Moreover, our findings may be relevant for policymakers when designing policies regarding the availability of emergency or support services. The mechanisms underlying the progression towards suicide attempts and the temporal dynamics of suicidal thinking remain a poorly understood phenomenon. Thus, it is crucial for researchers to further advance our understanding of implicit and explicit suicide cognition by using advanced cutting-edge forecasting models, such as Prophet.

References

1. World Health Organization. Public health action for the prevention of suicide: a framework. World Health Organization; 2012. Accessed March 26, 2021. http://apps.who.int/iris/bitstream/10665/75166/1/9789241503570_eng.pdf
2. Hedegaard H, Curtin SC, Warner M. Suicide rates in the United States continue to increase. *NCHS Data Brief* 2018;(309):8.
3. Hedegaard H, Curtin SC, Warner M. Increase in suicide mortality in the United States, 1999–2018. *NCHS Data Brief* 2020;(362). <https://stacks.cdc.gov/view/cdc/86670>
4. Mok PLH, Kapur N, Windfuhr K, et al. Trends in national suicide rates for Scotland and for England & Wales, 1960–2008. *Br J Psychiatry* 2012;200(3):245-251. doi:10.1192/bjp.bp.111.092908
5. Weinberger AH, Gbedemah M, Martinez AM, Nash D, Galea S, Goodwin RD. Trends in depression prevalence in the USA from 2005 to 2015: widening disparities in vulnerable groups. *Psychol Med* 2018;48(8):1308-1315. doi:10.1017/S0033291717002781
6. Bell DNF, Blanchflower DG. The well-being of the overemployed and the underemployed and the rise in depression in the UK. *J Econ Behav Organ* 2019;161:180-196. doi:10.1016/j.jebo.2019.03.018
7. Handley T, Rich J, Davies K, Lewin T, Kelly B. The challenges of predicting suicidal thoughts and behaviours in a sample of rural Australians with depression. *Int J Environ Res Public Health* 2018;15(5). doi:10.3390/ijerph15050928
8. Franklin JC, Ribeiro JD, Fox KR, et al. Risk factors for suicidal thoughts and behaviors: A meta-analysis of 50 years of research. *Psychol Bull* 2017;143(2):187-232. doi:10.1037/bul0000084
9. Hawton K, Bergen H, Cooper J, et al. Suicide following self-harm: Findings from the multicentre study of self-harm in England, 2000–2012 *J Affect Disord*. 2015;175:147-151. doi:10.1016/j.jad.2014.12.062
10. Foster T, Gillespie K, McClelland R. Mental disorders and suicide in Northern Ireland. *Br J Psychiatry* 1997;170(5):447-452. doi:10.1192/bjp.170.5.447
11. Potter LB, Powell KE, Kachur SP. Suicide prevention from a public health perspective. *suicide life threat behav* 1995;25(1):82-91. doi:<https://doi.org/10.1111/j.1943-278X.1995.tb00394.x>
12. Blaauw E, Arensman E, Kraaij V, Winkel FW, Bout R. Traumatic life events and suicide risk among jail inmates: The influence of types of events, time period and significant others. *J Trauma Stress* 2002;15(1):9-16. doi:<https://doi.org/10.1023/A:1014323009493>
13. Cooper J, Appleby L, Amos T. Life events preceding suicide by young people. *Soc Psychiatry Psychiatr Epidemiol* 2002;37(6):271-275. doi:10.1007/s001270200019

14. Reeves A, Stuckler D, McKee M, Gunnell D, Chang S-S, Basu S. Increase in state suicide rates in the USA during economic recession. *The Lancet* 2012;380(9856):1813-1814. doi:10.1016/S0140-6736(12)61910-2
15. Coimbra DG, Pereira e Silva AC, de Sousa-Rodrigues CF, et al. Do suicide attempts occur more frequently in the spring too? A systematic review and rhythmic analysis. *J Affect Disord* 2016;196:125-137. doi:10.1016/j.jad.2016.02.036
16. Christodoulou C, Efstathiou V, Bouras G, Korkoliakou P, Lykouras L. Seasonal variation of suicide: A brief review. *Encephalos* 2012;49:73-79.
17. Preti A. The influence of seasonal change on suicidal behaviour in Italy. *J Affect Disord*. 1997;44(2):123-130. doi:10.1016/S0165-0327(97)00035-9
18. Rocchi MBL, Sisti D, Cascio MT, Preti A. Seasonality and suicide in Italy: amplitude is positively related to suicide rates. *J Affect Disord* 2007;100(1):129-136.
19. Callanan VJ, Davis MS. Gender differences in suicide methods. *Soc Psychiatry Psychiatr Epidemiol* 2012;47(6):857-869.
20. Mościcki EK. Gender differences in completed and attempted suicides. *Ann Epidemiol* 1994;4(2):152-158.
21. Värnik P. Suicide in the world. *Int J Environ Res Public Health*. 2012;9(3):760-771.
22. Postolache TT, Mortensen PB, Tonelli LH, et al. Seasonal spring peaks of suicide in victims with and without prior history of mood disorders. *J Affect Disord* 2010;121(1-2):88-93.
23. Postolache TT, Mortensen PB, Tonelli LH, et al. Seasonal spring peaks of suicide in victims with and without prior history of hospitalization for mood disorders. *J Affect Disord* 2010;121(1):88-93.
24. Woo J-M, Okusaga O, Postolache TT. Seasonality of suicidal behavior. *Int J Environ Res Public Health* 2012;9(2):531-547.
25. Jacobsen FM, Wehr TA, Sack DA, James SP, Rosenthal NE. Seasonal affective disorder: a review of the syndrome and its public health implications. *Am J Public Health* 1987;77(1):57-60.
26. Spooon MR, Depue RA, Krauss SS. Dimensional measurement of seasonal variation in mood and behavior. *Psychiatry Res* 1991;39(3):269-284.
27. Hegde AL, Woodson H. Prevalence of seasonal changes in mood and behavior during the winter months in central Texas. *Psychiatry Res* 1996;62(3):265-271.
28. Wilkins CH, Sheline YI, Roe CM, Birge SJ, Morris JC. Vitamin D Deficiency Is associated with low mood and worse cognitive performance in older adults. *Am J Geriatr Psychiatry* 2006;14(12):1032-1040.
29. Valtonen H, Suominen K, Partonen T, Ostamo A, Lönnqvist J. Time patterns of attempted suicide. *J Affect Disord* 2006;90(2):201-207.

30. Chiu LPW. Do weather, day of the week, and address affect the rate of attempted suicide in Hong Kong? *Soc Psychiatry Psychiatr Epidemiol* 1988;23(4):229-235.
31. Ceccato V, Uittenbogaard A. Suicides in commuting railway systems: The case of Stockholm county, Sweden. *J Affect Disord* 2016;198:206-221.
32. Maldonado G, Kraus JF. Variation in suicide occurrence by time of day, day of the week, month, and lunar phase. *Suicide Life Threat Behav* 1991;21(2):174-187.
33. Nakamura JW, McLeod CR, McDermott JF. Temporal variation in adolescent suicide attempts. *Suicide Life Threat Behav* 1994;24(4):343-349.
34. Law C, De Leo D. Seasonal differences in the day-of-the-week pattern of suicide in Queensland, Australia. *Int J Environ Res Public Health* 2013;10(7):2825-2833.
35. Su MK, Chan PY, Hoffman RS. The seasonality of suicide attempts: a single poison control center perspective. *Clin Toxicol* 2020;58(11):1034-1041.
36. Beauchamp GA, Ho ML, Yin S. Variation in suicide occurrence by day and during major American holidays. *J Emerg Med* 2014;46(6):776-781.
37. Akkaya-Kalayci T, Kapusta ND, Waldhör T, Blüml V, Poustka L, Özlü-Erkilic Z. The association of monthly, diurnal and circadian variations with suicide attempts by young people. *Child Adolesc Psychiatry Ment Health* 2017;11(1):35.
38. Doganay Z, Sunter AT, Guz H, et al. Climatic and diurnal variation in suicide attempts in the ED. *Am J Emerg Med* 2003;21(4):271-275.
39. Preti A, Miotto P. Diurnal variations in suicide by age and gender in Italy. *J Affect Disord* 2001;65(3):253-261.
40. van Houwelingen CAJ, Beersma DGM. Seasonal changes in 24-h patterns of suicide rates: a study on train suicides in The Netherlands. *J Affect Disord* 2001;66(2):215-223.
41. Altamura C, VanGastel A, Pioli R, Mannu P, Michael Maes. Seasonal and circadian rhythms in suicide in Cagliari, Italy. *J Affect Disord* 1999;53(1):77-85.
42. Murray G, Allen NB, Trinder J. Seasonality and circadian phase delay: prospective evidence that winter lowering of mood is associated with a shift towards eveningness. *J Affect Disord* 2003;76(1):15-22.
43. Bahk Y-C, Han E, Lee S-H. Biological rhythm differences and suicidal ideation in patients with major depressive disorder. *J Affect Disord* 2014;168:294-297.
44. Kim JS, Ha TH, Chang JS, et al. Seasonality and its distinct clinical correlates in bipolar II disorder. *Psychiatry Res* 2015;225(3):540-544.
45. Rumble ME, Dickson D, McCall WV, et al. The relationship of person-specific eveningness chronotype, greater seasonality, and less rhythmicity to suicidal behavior: a literature review. *J Affect Disord* 2018;227:721-730.

46. Glenn JJ, Werntz AJ, Slama SJK, Steinman SA, Teachman BA, Nock MK. Suicide and self-injury-related implicit cognition: A Large-scale examination and replication. *J Abnorm Psychol* 2017;126(2):199-211.
47. Glenn CR, Millner AJ, Esposito EC, Porter AC, Nock MK. Implicit identification with death predicts suicidal thoughts and behaviors in adolescents. *J Clin Child Adolesc Psychol* 2019;48(2):263-272.
48. Nock MK, Park JM, Finn CT, Deliberto TL, Dour HJ, Banaji MR. Measuring the suicidal mind: Implicit cognition predicts suicidal behavior. *Psychol Sci* 2010;21(4):511-517.
49. Tello N, Harika-Germaneau G, Serra W, Jaafari N, Chatard A. Forecasting a fatal decision: direct replication of the predictive validity of the suicide–implicit association test. *Psychol Sci* 2020;31(1):65-74.
50. Charlesworth TES, Banaji MR. Patterns of implicit and explicit attitudes: I. Long-term change and stability from 2007 to 2016. *Psychol Sci* 2019;30(2):174-192.
51. Greenwald AG, McGhee DE, Schwartz JL. Measuring individual differences in implicit cognition: the implicit association test. *J Pers Soc Psychol* 1998;74(6):1464-1480.
52. O'Shea BA, Glenn JJ, Millner AJ, Teachman BA, Nock MK. Decomposing implicit associations about life and death improves our understanding of suicidal behavior. *Suicide Life Threat Behav* 2020;50(5):1065-1074.
53. Millner AJ, Coppersmith DDL, Teachman BA, Nock MK. The Brief Death Implicit Association Test: Scoring recommendations, reliability, validity, and comparisons with the Death Implicit Association Test. *Psychol Assess* 2018;30(10):1356-1366.
54. Greenwald AG, Nosek BA, Banaji MR. Understanding and using the Implicit Association Test: I. An improved scoring algorithm. *J Pers Soc Psychol* 2003;85(2):197-216.
55. Cha CB, Glenn JJ, Deming CA, et al. Examining potential iatrogenic effects of viewing suicide and self-injury stimuli. *Psychol Assess* 2016;28(11):1510-1515.
56. Nock MK, Holmberg EB, Photos VI, Michel BD. Self-Injurious thoughts and behaviors interview: development, reliability, and validity in an adolescent sample. *Psychol Assess* 2007;19(3):309-317.
57. Taylor SJ, Letham B. Forecasting at scale. *Am Stat.* 2018;72(1):37-45.
58. Xie C, Wen H, Yang W, et al. Trend analysis and forecast of daily reported incidence of hand, foot and mouth disease in Hubei, China by Prophet model. *Sci Rep* 2021;11(1):1445.
59. Aditya Satrio CB, Darmawan W, Nadia BU, Hanafiah N. Time series analysis and forecasting of coronavirus disease in Indonesia using ARIMA model and PROPHET. *Procedia Comput Sci* 2021;179:524-532.
60. Shumway RH, Stoffer DS. ARIMA Models. In: Shumway RH, Stoffer DS, eds. *Time series analysis and its applications: with R examples*. Springer Texts in Statistics. Springer International Publishing; 2017:75-163.

61. Tsouvelas G, Giotakos O, Massou E, Konstantakopoulos G. Seasonality and time-related aspects of suicides in Greece: an applied time-series analysis. *Dialogues Clin Neurosci Ment Health* 2019;2(1):01-11.
62. Benjamini Y, Hochberg Y. Controlling the false discovery rate: A practical and powerful approach to multiple testing. *J R Stat Soc Ser B Methodol* 1995;57(1):289-300.
63. Zheng H, Echave P. Are recent cohorts getting worse? Trends in U.S. adult physiological status, mental health, and health behaviors across a century of birth cohorts. *Am J Epidemiol* 2021;(kwab076).
64. Twenge JM, Cooper AB, Joiner TE, Duffy ME, Binau SG. Age, period, and cohort trends in mood disorder indicators and suicide-related outcomes in a nationally representative dataset, 2005–2017. *Journal of Abnormal Psychology* 2018;128: 185-199.
65. Hong J, Knapp M, McGuire A. Income-related inequalities in the prevalence of depression and suicidal behaviour: a 10-year trend following economic crisis. *World Psychiatry* 2011;10(1):40-44.
66. Jeste DV, Lee EE, Cacioppo S. Battling the modern behavioral epidemic of loneliness: suggestions for research and interventions. *JAMA Psychiatry* 2020;77(6):553-554.
67. Santos HC, Varnum MEW, Grossmann I. Global increases in individualism. *Psychol Sci* 2017;28(9):1228-1239.
68. Sohn SY, Rees P, Wildridge B, Kalk NJ, Carter B. Prevalence of problematic smartphone usage and associated mental health outcomes amongst children and young people: a systematic review, meta-analysis and GRADE of the evidence. *BMC Psychiatry* 2019;19(1):356.
69. Kurdi B, Ratliff KA, Cunningham WA. Can the Implicit Association Test serve as a valid measure of automatic cognition? A response to Schimmack (2021). *Perspect Psychol Sci* 2021;16(2):422-434.
70. Connor P, Evers ERK. The bias of individuals (in crowds): why implicit bias is probably a noisily measured individual-level construct. *Perspect Psychol Sci* 2020;15(6):1329-1345.
71. Darling-Hammond S, Michaels EK, Allen AM, et al. After “The China Virus” went viral: racially charged coronavirus coverage and trends in bias against Asian Americans. *Health Educ Behav* 2020;47(6):870-879.
72. Ravary A, Baldwin MW, Bartz JA. Shaping the body politic: mass media fat-shaming affects implicit anti-fat attitudes. *Pers Soc Psychol Bull* 2019;45(11):1580-1589.
73. Ofosu EK, Chambers MK, Chen JM, Hehman E. Same-sex marriage legalization associated with reduced implicit and explicit antigay bias. *Proc Natl Acad Sci* 2019;116(18):8846-8851.
74. Trope Y, Liberman N. Construal-level theory of psychological distance. *Psychol Rev* 2010;117(2):440-463.

75. Jick H. Antidepressants and the risk of suicidal behaviors. *JAMA* 2004;292(3):338.
76. Forte A, Buscagioni A, Fiorillo A, Pompili M, Baldessarini RJ. Suicidal risk following hospital discharge: A review. *Harv Rev Psychiatry* 2019;27(4):209-216.
77. Fruehwald S, Frottier P, Matschnig T, Koenig F, Lehr S, Eher R. Do monthly or seasonal variations exist in suicides in a high-risk setting? *Psychiatry Res* 2004;121(3):263-269.
78. Di Nicola M, Mazza M, Panaccione I, et al. Sensitivity to climate and weather changes in euthymic bipolar subjects: association with suicide attempts. *Front Psychiatry* 2020;11.
79. Murray G, Allen NB, Trinder J. A longitudinal investigation of seasonal variation in mood. *Chronobiol Int* 2001;18(5):875-891.
80. Hjorthol R. Winter weather – an obstacle to older people’s activities? *J Transp Geogr* 2013;28:186-191.
81. Magnusson A, Boivin D. Seasonal affective disorder: an overview. *Chronobiol Int* 2003;20(2):189-207.
82. O’Shea BA, Watson DG, Brown GDA, Fincher CL. Infectious disease prevalence, not race exposure, predicts both implicit and explicit racial prejudice across the United States. *Soc Psychol Personal Sci* 2020;11(3):345-355.
83. Giasson HL, Chopik WJ. Geographic patterns of implicit age bias and associations with state-level health outcomes across the United States. *Eur J Soc Psychol* 2020;50(6):1173-1190.
84. Ryu S, Lee H, Lee D-K, Kim S-W, Kim C-E. Detection of suicide attempters among suicide ideators using machine learning. *Psychiatry Investig* 2019;16(8):588-593.